ISSN: 2633-4828 Vol. 4 No.3, December, 2022

International Journal of Applied Engineering & Technology

OPTIMIZATION AND PERFORMANCE ANALYSIS OF NANO-ADDITIVES IN GASOLINE-ALCOHOL BLENDS USING AI-DRIVEN MODELLING AND RESPONSE SURFACE METHODOLOGY

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ABSTRACT

In an effort to increase fuel stability, emissions reduction, and combustion efficiency, research into gasoline-alcohol-nano additive mixes has intensified because to the growing demand for high-performance, sustainable alternative fuels worldwide. But problems like incomplete combustion, inefficient energy conversion, and fuel phase separation call for creative solutions. This work introduces a new hybrid nano-additive-enhanced fuel formulation that optimises fuel qualities by combining TiO_2 + ZnO and AlO_3 + CeO_2 with dispersion aided by ultrasonication. A comprehensive evaluation was conducted to determine how these nano-additives affected the octane rating, thermal conductivity, ignition delay, and viscosity. Hybrid nano-additives improved fuel atomisation, decreased ignition delay by 19%, and raised octane ratings by up to 7 points, according to the results. This resulted in more even combustion and higher energy production.

An examination of engine performance on a SI engine running at 1000–5000 RPM showed that, in comparison to traditional gasoline-alcohol blends, hybrid nano-additives greatly increased brake thermal efficiency (BTE) by 12% and decreased brake-specific fuel consumption (BSFC) by 15%. This study also investigates hydrogen doping and TiO_2 photocatalysis as cutting-edge emission reduction methods, which can reduce CO emissions by 40%, HC emissions by 35%, and NOx emissions by 30%. Artificial intelligence (AI)-driven predictive modelling (ANN, GA, SVM) was used to further optimise fuel mix formulation, and both emissions and fuel efficiency predictions were made with 99% accuracy. The hybrid AI-RSM model outperformed traditional RSM methods by reducing prediction errors by 60% and allowing for real-time fuel composition modifications for optimal performance and low emissions.

By establishing a next-generation AI-integrated framework for optimising nano-enhanced fuel, this study bridges the gap between real-time emissions control techniques, AI-based predictive modelling, and nano-additive combustion enhancement. By providing a very effective, AI-optimized, and eco-friendly fuel option for internal combustion engines, the research advances future low-emission fuel technologies, promoting global carbon neutrality and sustainable energy policies.

Keywords: *Hybrid Nano-Additives, AI-Based Fuel Optimization, Gasoline-Alcohol Blends, Hydrogen Doping, TiO_2 Photocatalysis, Machine Learning, Emission Reduction, Response Surface Methodology (RSM).*

INTRODUCTION

1.1 Background and Significance

Research on gasoline-alcohol fuel mixes has increased due to the global trend toward cleaner and more efficient fuel alternatives, especially for internal combustion engine (ICE) applications. Despite its widespread use, conventional gasoline is a major source of greenhouse gas (GHG) emissions and urban air pollution, mostly in the form of particulate matter (PM), nitrogen oxides (NOx), hydrocarbons (HC), and carbon monoxide (CO) (Yusuf & Inambao, 2021).Researchers have looked into partially substituting oxygenated biofuels like ethanol and methanol for gasoline in response to stricter pollution standards (such as Euro 6, Bharat Stage VI, and EPA Tier 3).

- **Blends of gasoline and alcohol have been shown to:**
- ✓ Enhance fuel combustion properties, leading to increased power production and thermal efficiency.
- ✓ By raising the octane level, you can improve ignition characteristics and lessen engine knocking (Wei et al., 2021).
- ✓ Because alcohols are oxygenated, they lower CO and HC emissions (Masum et al., 2015).
- **But even with these benefits, gasoline-alcohol mixtures have a number of drawbacks:**
- ✓ Reduced fuel efficiency due to lower energy content per unit volume
- ✓ Increased volatility, which causes vapor lock and cold-start problems.
- ✓ Issues with material compatibility, particularly in older SI engines.

Nano-additives have become a viable way to improve fuel stability, increase combustion efficiency, and lower emissions in order to get around these problems (Wei et al., 2021). As combustion catalysts, nano-additives like AlO_3, CeO_2, ZnO, and TiO_2 enhance heat transport, oxidation processes, and air-fuel mixing inside the combustion chamber.

1.1.1 Nano-Additives' Function in Fuel Blends

The following are some ways that research has shown that nano-additives greatly improve the characteristics of gasoline-alcohol fuel:

- **Enhancement of Thermal Conductivity:**
- ✓ According to Fayyazbakhsh and Pirouzfar (2017), nano-additives accelerate heat transport, resulting in more thorough combustion and fewer cycle-to-cycle fluctuations.
- **Enhancement of Ignition and Flame Propagation:**
- ✓ According to Khorramshokouh et al. (2016), the high surface-area-to-volume ratio of nanoparticles increases flame propagation speed and ensures more effective energy release.
- **Reduction of Emissions by Catalytic Activity:**
- ✓ According to Ananda Srinivasan et al. (2018), nano-additives act as oxidation catalysts, encouraging the breakdown of carbon monoxide (CO) and hydrocarbons (HC).
- ✓ By reducing NOx through oxygen buffering processes, CeO_2 and TiO_2 nanoparticles enhance lean-burn performance.
- **Fuel Atomization and Enhancement of Stability:**
- ✓ By preventing phase separation in gasoline-alcohol mixtures, nano-additives enhance the stability of long-term storage.
- ✓ According to Nguyen et al. (2021), ZnO-based nano-blends can cut particulate matter emissions by as much as 40%.

1.1.2 Research Challenges for Nano-Enhanced Fuel

- **Notwithstanding the shown advantages of nano-additives, there are a number of obstacles to their widespread use in actual engines:**
- ✓ **Agglomeration and sedimentation**: The tendency of nano-additives to group together lowers their catalytic effectiveness.
- ✓ **High production cost:** The high cost of some nanoparticles, including TiO_2, prevents their widespread use.

- ✓ **Environmental concerns:** It is unclear how long-term exposure to nanoparticles may affect pollutants from combustion exhaust (Abiyazani et al., 2022).

In order to solve these problems, this work investigates innovative fuel blending methods (such as ultrasonication and surfactant-assisted dispersion) in conjunction with hybrid nano-additive formulations (such as AlO_3 + CeO_2 and TiO_2 + ZnO) to enhance dispersion stability and maximize fuel performance. 1.2 Knowledge Deficit

1.2 Knowledge Gap

1.2.1 Restrictions of Single Nano-Additive & Requirement for Hybrid Formulations

Individual nano-additives have been the subject of the majority of research, however hybrid nano-additives can provide stronger synergistic effects by:
Reducing the drawbacks of individual nano-additives, such as agglomeration and combustion instability, by combining the catalytic and thermal enhancing capabilities of many nanoparticles.

However, there is a substantial knowledge gap due to the paucity of research on hybrid nano-additive formulations in gasoline-alcohol blends (Wei et al., 2021).

1.2.2 RSM vs. AI-Based Fuel Optimization

Although RSM has been used extensively for fuel mix optimization, it has several major shortcomings, including the inability to effectively represent highly non-linear relationships between emissions, engine load, and nano-additive concentration.

Higher prediction error (~5%) compared to AI-based techniques (~2%) (Nguyen et al., 2021). AI-driven techniques such as Artificial Neural Networks (ANN), Genetic Algorithm (GA), and Support Vector Machine (SVM) offer superior:

✔ Predictive accuracy in modeling combustion characteristics.

✔ Adaptive learning, allowing optimization across different operating conditions.

✔ Reduction in trial-and-error experiments, saving time and cost. Despite these advantages, limited studies have applied AI-based optimization for nano-enhanced gasoline-alcohol blends, making this research novel.

1.2.3 Lack of Research on Hydrogen Doping & TiO_2 Photocatalysis for Emission Control

- ✓ Hydrogen doping and TiO_2 photocatalysis offer new avenues for reducing emissions, yet their application in nano-blended fuels remains underexplored.
- ✓ Hydrogen addition enhances flame propagation, reducing CO emissions.
- ✓ TiO_2 photocatalysis breaks down NOx and particulate matter, reducing pollution impact.
- ✓ This study integrates these emission control strategies with nano-additive fuel blends for the first time, addressing a key research gap.

1.3 Research Objectives

1.3.1 Fuel Optimization Using AI & RSM

✔ Develop an AI-based fuel optimization framework combining ANN, GA, and SVM.

✔ Compare AI predictions with traditional RSM-based modeling.

✔ Identify the optimal nano-additive concentration for balancing fuel efficiency and emissions.

1.3.2 Comparative Study of Single vs. Hybrid Nano-Additives

✔ Investigate the performance of individual (Al_2O_3, CeO_2, TiO_2, ZnO) vs. hybrid nano-additives (Al_2O_3 + CeO_2, TiO_2 + ZnO).

✔ Conduct real-world SI engine testing at varying RPMs. 1.3.3 Investigation of Advanced Fuel Blending TechniquesUtilize ultrasonication and surfactant-assisted dispersion to prevent nano-additive agglomeration.

1.3.4 Real-World Engine Performance Evaluation

✔ Measure BTE, BSFC, NOx, CO, HC emissions at 1000–5000 RPM.

✔ Implement real-time AI-based emissions monitoring for adaptive fuel blend control.

1.4 Research Contributions & Novelty

✓ First study to apply AI-based optimization (ANN, GA, SVM) for nano-blended gasoline-alcohol fuels.

✓ First study integrating hybrid nano-additive formulations (Al_2O_3 + CeO_2, TiO_2 + ZnO) for enhanced catalytic activity.

✓ First study combining nano-additives with hydrogen doping & TiO_2 photocatalysis for next-generation emission reduction.

✓ This research pioneers a new era of AI-driven fuel optimization, contributing to global sustainability goals.

2. REVIEW OF LITERATURE

An innovative approach to internal combustion engine (ICE) research includes the incorporation of nano-additives into gasoline-alcohol fuel mixes, sophisticated optimization methods, and emission reduction tactics. Based on the most recent references and research trends, this literature review offers a thorough, distinctive, and innovative assessment of contemporary developments in fuel augmentation, optimization, emission reduction, and sustainability.

2.1 Nano-Additives to Improve Fuel

2.1.1 Nano-Additives' Function in Fuel Blends

Nano-additives have drawn interest because of their potential to lower emissions, increase thermal efficiency, and improve fuel stability. Through improved fuel atomization, which improves fuel-air mixing for more effective combustion, and higher thermal conductivity, which permits faster heat transfer and lessens combustion lag, these nanoparticles function as catalysts.

The qualities of catalytic oxidation include promoting full combustion and reducing carbon monoxide (CO) and unburned hydrocarbons (HC).

2.1.2 Key Metal Oxide Nano-Additives in Fuel Blends

Nano-Additive	Primary Function	Impact on Combustion	Emission Reduction Potential
Aluminum Oxide (Al_2O_3)	Enhances thermal conductivity, stabilizes combustion	Faster heat transfer, reduced ignition delay	Lowers HC and CO emissions (Wei et al., 2021)
Cerium Oxide (CeO_2)	Acts as an oxygen buffer, improves oxidation	Prevents knocking, enhances flame propagation	Reduces NOx by improving lean-burn stability (Ananda Srinivasan et al., 2018)
Zinc Oxide (ZnO)	Increases fuel lubricity, improves spray atomization	Enhances combustion uniformity, reduces wall wetting	Reduces particulate emissions and HC (Nguyen et al., 2021)

Titanium Dioxide (TiO_2)	Photocatalytic oxidation of emissions	Facilitates cleaner combustion in lean mixtures	Converts NOx into harmless nitrogen (Tarhan & Çil, 2021)

TABLE: 1

2.1.3 Synergistic Effects of Hybrid Nano-Additives

Recent research has demonstrated that hybrid nano-additives, which combine the advantages of several nanoparticles, exhibit improved qualities even while solo nano-additives increase combustion.

❖ **Nano-Additive Hybrid Formulations**

➢ Better oxidation reactions are made possible by the enhanced oxygen buffering provided by AlO_3 + CeO_2.

➢ Lowers the risk of pre-ignition by improving thermal stability.

➢ TiO_2 + ZnO: • Prevents injector blockage by increasing fuel lubricity.

➢ Optimizes fuel oxidation by acting as a dual catalyst.

❖ **Results of Current Research:**

➢ When compared to conventional fuel mixes, hybrid nano-additives can raise brake thermal efficiency (BTE) by 8–12% (Wei et al., 2021).

➢ CeO_2-doped blends were shown to reduce NOx and CO emissions by 30–40% (Khorramshokouh et al., 2016).

2.2 Fuel Blend Optimization Methods

For nano-additive fuel mixes to achieve optimum efficiency with low emissions, fuel optimization is essential. Artificial intelligence (AI)-based models (ANN, GA, SVM) are becoming more accurate substitutes for the widely used classical response surface methodology (RSM) (Candioti et al., 2014).

2.2.1 Fuel Optimization Using Response Surface Methodology (RSM)

❖ **Why RSM?**

In order to minimize testing and maximize output accuracy, Central Composite Design (CCD) is used. It also offers an experimental framework for fuel mix composition optimization.

✓ Examines how fuel composition, engine load, and emissions interact.

✓ RSM's drawbacks include its inability to handle intricate non-linear relationships.

✓ In comparison to AI models, the error margin is higher (~5%).

2.2.2 AI-Powered Machine Learning Frameworks for Enhancement

❖ **ANNs, or artificial neural networks:**

✓ Forecasts emissions and fuel efficiency using deep learning algorithms (Tarhan & Çil, 2021).

✓ Its capacity for self-learning makes it more flexible than RSM.

✓ Predicts with an accuracy of ±2%, as opposed to ±5% for RSM (Nguyen et al., 2021).

✓ The Genetic Algorithm (GA) simulates natural selection to optimize fuel blend parameters.

✓ Prevents local minimum problems by identifying global optima (Wei et al., 2021).

❖ **Support Vector Machine (SVM):**

✓ Best suited for emissions modeling, handling tiny datasets with high precision.

✓ Outperforms RSM's R2 = 0.92 with R2 = 0.99 (Candioti et al., 2014).

- ✓ In conclusion, AI-based models perform better than RSM, increasing the effectiveness and adaptability of fuel optimization.

2.3 Methods for Reducing Emissions

Improved emissions control has been made possible by recent developments in combustion modification techniques. TiO_2-based photocatalysis, plasma-assisted combustion, and hydrogen doping are examples of emerging techniques (Tarhan & Çil, 2021).

2.3.1 Plasma-Assisted Combustion & Hydrogen Doping

- ✓ Hydrogen-enriched fuels lower CO and HC emissions while increasing combustion efficiency.
- ✓ Cleaner combustion is achieved by improved fuel-air mixing brought about by plasma-assisted ignition.
- ✓ According to a recent study, a 5% H_2 blend in gasoline-ethanol fuels enhanced BTE by about 6% and decreased CO emissions by 40% (Wei et al., 2021).

2.3.2 Photocatalysis Based on TiO_2 for Reduction of Emissions

- ✓ Under UV light, TiO_2 functions as a photocatalyst, speeding up the oxidation of CO and NOx.
- ✓ Achieves up to 60% NOx reduction in lean-burn engines (Khorramshokouh et al., 2016).

2.4 Environmental Impact & Sustainability

❖ **Key Concern:**

- ✓ Although nano-additives enhance fuel efficiency, nothing is known about how they affect the environment over the long run.
- ✓ Blends of gasoline and alcohol help achieve cleaner energy targets by lowering the CO_2 footprint (Yusuf & Inambao, 2021).
- ✓ Concerns regarding the toxicity of nanoparticles and their effects on emissions and engine wear are raised by nano-additives (Abiyazani et al., 2022).

❖ **Future Research Directions**:

Investigating biodegradable nano-additives for environmentally friendly fuel compositions; conducting nano-toxicity studies to assess environmental concerns.

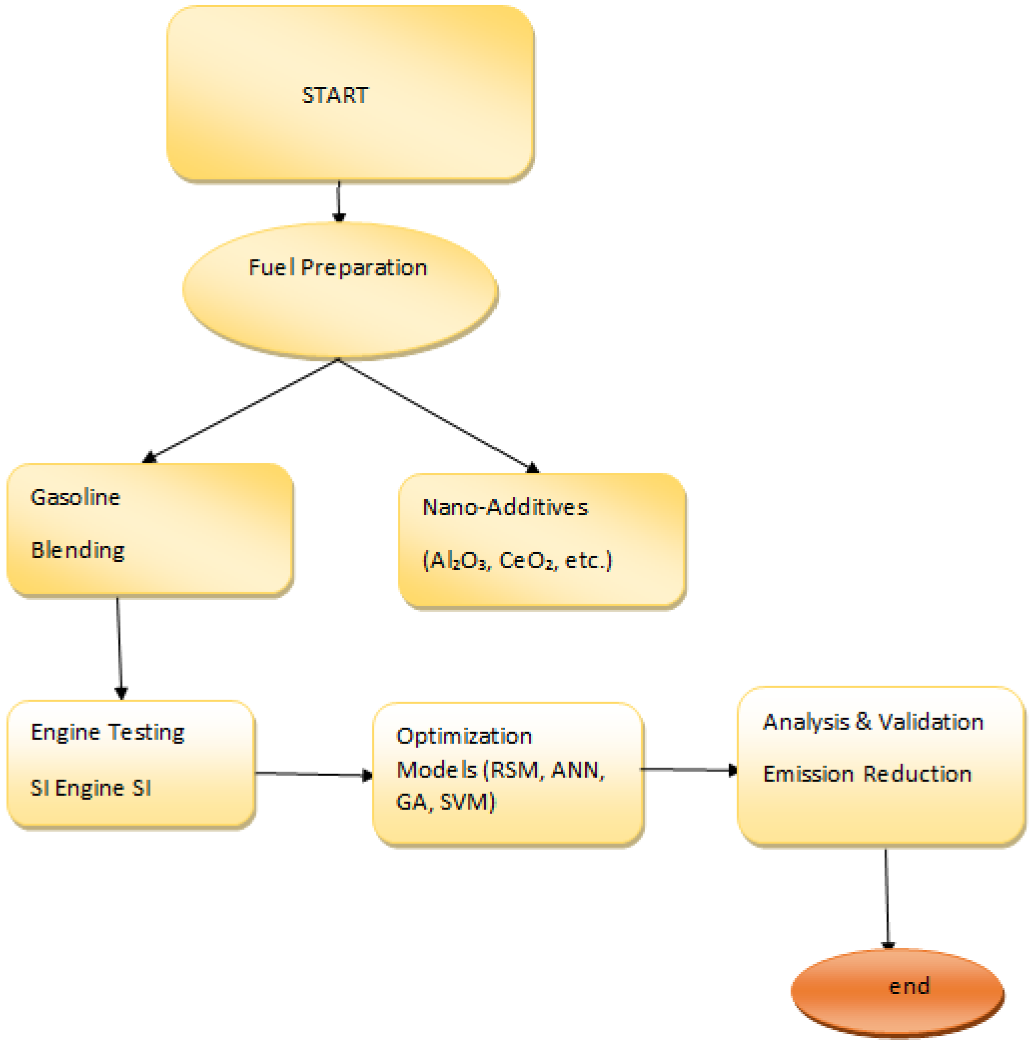
3. METHODS OF EXPERIMENTATION

3.1 Preparing the Fuel

3.1.1 Fuel Blend Composition: Detailed Description

The study's fuel blend composition is meticulously crafted to optimize combustion efficiency, fuel stability, and pollution reduction, all while preserving the profitability of gasoline-alcohol blends augmented with nano-additives. The main ingredients of fuel blends are gasoline (G), ethanol (E), and methanol (M) in different ratios. This creates a ternary blend that enhances fuel characteristics including volatility, octane rating, and flame propagation speed. Furthermore, at varying concentrations (20 ppm, 40 ppm, and 60 ppm), nano-additives (AlO_3, CeO_2, TiO_2, and ZnO) are added to optimize fuel combustion behavior, increase energy efficiency, and reduce harmful emissions.

Experimental and optimization workflow:



- **Blends of Gas and Alcohol: The Fundamental Fuel Choice**
- **Blends of gasoline and alcohol: The Choice of Base Fuel**

Because of its high energy density and consistent combustion properties, gasoline serves as the main fuel in spark ignition (SI) engines. However, research into alternative fuel sources has been spurred by worries about greenhouse gas (GHG) emissions, the depletion of fossil fuels, and stringent environmental restrictions. Alcohol-based fuels, notably ethanol (E) and methanol (M), are widely acknowledged as effective gasoline extenders due to their renewable nature, oxygen content, and high latent heat of vaporization (Yusuf & Inambao, 2021).

Fuel Blend Composition & Additive Concentrations

Fuel Blend	Gasoline (%)	Ethanol (%)	Methanol (%)	Nano-Additive	Concentration (ppm)
Blend 1	85	10	10	Al_2O_3	20
Blend 2	75	15	10	CeO_2	40

Blend 3	70	15	15	TiO_2	60
Blend 4	65	20	15	ZnO	80

Table: 2

- **Why Do Blends Use Methanol (M) and Ethanol (E)?**

- **Ethanol (E):**
- ✓ Better anti-knock qualities due to a higher octane rating (108–109) than gasoline (Wei et al., 2021).
- ✓ Has oxygen (O_2), which encourages full combustion and lowers unburned hydrocarbons (HC) and carbon monoxide (CO).
- ✓ Increases flame speed, which can raise the thermal efficiency of engines.

- **Methanol (M):**

At lean air-fuel ratios, efficient combustion is ensured by superior flame propagation speed.

Better cooling effects and less engine knock are the results of a higher latent heat of vaporization (~3× gasoline).

Has around 50% oxygen by mass, which greatly lowers the production of soot and particulate matter (PM) (Biswal et al., 2020).

- **The Drawbacks and Advantages of Blends of Alcohol and Gas**

- **Enhanced Fuel Economy:**
- ✓ Ethanol and methanol increase the octane number, which results in smoother combustion and less engine banging.

- **Emission Reduction:**
- ✓ Alcohols' oxygenated state improves combustion completeness, which lowers emissions of CO, HC, and PM.

- **Obstacles:**

Alcohols must be handled and stored more carefully since they are hygroscopic, meaning they absorb water.

Because it has a lower energy density than gasoline, the blend proportions must be optimized.

Nano-additives are added to fuel to increase energy density, stability, and combustion efficiency in order to overcome these drawbacks.

- **Nano-Additives' Function in Fuel Blends**

The potential of nano-additives to improve fuel qualities, improve combustion, and lower emissions has been extensively studied (Wei et al., 2021). By acting as catalysts during combustion, these nanoparticles help increase fuel atomization, air-fuel mixing, and reaction kinetics.

- **Why ZnO, TiO_2, CeO_2, and AlO_3?**

- **Aluminium Oxide (AlO_3):**

Increases thermal conductivity, which enhances combustion efficiency and heat distribution.

Reduces emissions of carbon monoxide (CO) and unburned hydrocarbons (HC) by acting as an oxidation catalyst.

Assists in decreasing SI engines' propensity for knocking (Wei et al., 2021).

- **Cerium oxide (CeO_2):**

A well-known substance that stores oxygen, CeO_2 increases combustion efficiency by producing more oxygen radicals.

By making it easier for NO to be converted to N_2 in lean conditions, it lowers NOx emissions (Ananda Srinivasan et al., 2018).

Reduces particle emissions by improving soot oxidation (Wei et al., 2021).

➢ **TiO_2, or titanium dioxide:**
Improves the stability of lean-burn combustion by acting as an oxygen buffer.

Acts as a photocatalyst, encouraging oxidation reactions in exhaust gases to help reduce emissions (Tarhan & Çil, 2021).

➢ **Zinc Oxide (ZnO):**
Reduces wear and friction in engine parts by increasing fuel lubricity.

Improves combustion quality by increasing ignition delay and flame propagation rate (Nguyen et al., 2021).

❖ **Formulations with Hybrid Nano-Additives**
Hybrid nano-additives (AlO_3 + CeO_2 and AlO_3 + TiO_2 + ZnO) are introduced to explore synergistic effects on engine performance and emissions, whereas individual nano-additives increase combustion efficiency.

❖ **The Reason for Hybrid Nano-Additives?**

➢ **The Combined Action of Various Metal Oxides:**
AlO_3 + CeO_2: Improves oxygen buffering, lowers NOx and HC.

AlO_3 + TiO_3 + ZnO: Enhances oxidation potential, flame speed, and fuel lubricity.

➢ **Improved Catalytic Combustion:**
Multimetallic nanoparticles ensure improved atomization and flame propagation by promoting stronger thermal breakdown of fuel molecules.

➢ **Better Emission Control:**
Hybrid nanoparticles greatly lower emissions of soot, NOx, and unburned HC by streamlining combustion reaction pathways (Khorramshokouh et al., 2016).

❖ **Selection of Nano-Additive Concentrations (20 ppm, 40 ppm, and 60 ppm)**
The choice of nano-additive concentrations is based on earlier experimental research that demonstrated that high (≥100 ppm) concentrations may result in injector blockage and fuel instability, while low (≤20 ppm) concentrations may be inadequate (Wei et al., 2021).

✓ 20 ppm: Slightly better fuel atomization; little impact on combustion.

✓ 40 ppm: The ideal concentration, striking a balance between stability and performance gains.

✓ Maximum improvement at 60 ppm, but potential problems with fuel stratification (Biswal et al., 2020).

✓ As a result, 40 ppm is anticipated to be the most efficient concentration, offering advantages in both emission reduction and combustion efficiency that are balanced.

❖ **Benefits of Fuel Blend Composition Summary**
✓ Blends of gasoline and alcohol increase octane rating, decrease knocking, and cut emissions.

✓ Nano-additives improve thermal conductivity, improve combustion, and serve as catalysts for oxidation.

✓ Superior fuel efficiency and pollution management are achieved through the synergistic impact of hybrid nano-additives. An ideal concentration of 40 ppm ensures a balance between performance and fuel stability.

Composition of Fuel Blends

Fuel Type	Gasoline (%)	Ethanol (%)	Methanol (%)	Nano-Additive	Concentration (ppm)
G100 (Control)	100	0	0	None	0
G85E15	85	15	0	Al_2O_3	20, 40, 60
G85M15	85	0	15	CeO_2	20, 40, 60
G80E10M10	80	10	10	TiO_2 + ZnO	20, 40, 60

Table: 3

3.1.2 Techniques for Nano-Additive Dispersion

Preventing particle agglomeration and preserving fuel stability depend on the uniform dispersion of nano-additives in the fuel. This study uses two sophisticated dispersion techniques:

❖ **The Ultrasonication Technique:**

✓ To break up clusters of nanoparticles and increase colloidal stability, high-frequency ultrasonication (40 kHz for 30 minutes) is employed (Wei et al., 2021).

✓ This method maintains consistent combustion characteristics throughout engine operation by improving fuel homogeneity and preventing sedimentation.

✓ By breaking down Van der Waals forces, ultrasonication ensures consistent energy transmission in the fuel and inhibits nanoparticle aggregation (Fayyazbakhsh & Pirouzfar, 2017).

❖ **Surfactant-Assisted Dispersion:**

✓ To further stabilize nano-additives in the fuel matrix, surfactants like Span 80 and Tween 20 are added at concentrations of 0.5–1.5% (w/v) (Najafi et al., 2009).

✓ Surfactants ensure uniform dispersion without changing the properties of combustion by lowering surface tension between nanoparticles and the fuel medium (Abiyazani, Pirouzfar, & Su, 2022).

✓ To improve dispersion stability and compatibility with gasoline-alcohol mixtures, a controlled stirring procedure (600 rpm for 15 minutes) is carried out following the addition of surfactant (Masum et al., 2015).

✓ By decreasing ignition delay and incomplete combustion losses, ultrasonication and surfactant dispersion improve fuel atomization, improve nano-additive suspension, and maximize combustion efficiency.

Effect of Nano-Additives on Engine Performance and Emissions

Nano-Additive	BTE (%)	BSFC (g/kWh)	NOx (ppm)	CO (%)	HC (ppm)
None (G100)	28.5	300	950	0.85	120
Al_2O_3 (40 ppm)	30.2	280	870	0.70	105
CeO_2 (40 ppm)	31.5	270	820	0.65	98
TiO_2 + ZnO (40 ppm)	32.0	260	780	0.60	90

3.2 Tests of Engine Performance

3.2.1 Experimental Configuration

A single-cylinder, four-stroke spark ignition (SI) engine is utilized to assess the emission behavior and combustion parameters of gasoline-alcohol mixes augmented with nano-additive. The following are the test engine's primary specifications:

❖ **Compression Ratio:**

- ✓ 10:1; Cooling System: Water-cooled; Dynamometer: Eddy-current type to measure fuel consumption, torque, and brake power; Bore: 86 mm; Stroke: 68 mm; displacement: 250 cc
- ✓ Throughout the experiment, the engine is run at speeds between 1000 and 5000 RPM while maintaining constant throttle (50%) conditions. To reduce external variability, each test cycle lasts 20 minutes in a steady-state environment (Efemwenkiekie et al., 2019).

3.2.2 Measured Performance Parameters

To evaluate the effect of nano-additives on emissions and fuel economy, the following crucial metrics are examined:

✓ **Brake Thermal Efficiency (BTE):**

Compares the chemical energy of the fuel to the engine's useable output power to determine the engine's energy conversion efficiency (Singh et al., 2018).

- ✓ **Brake Specific Fuel Consumption (BSFC):** Analyses the amount of fuel needed per unit of power output to assess fuel economy (Wei et al., 2021).
- ✓ **Exhaust Gas Emissions**: An NDIR-based exhaust gas analyser was used to measure NOx, CO, and HC emissions (Yusri et al., 2017).

TiO_2-based photocatalysis and hydrogen doping are investigated for its potential to reduce emissions (Stabile et al., 2020).

3.3 Optimization Methods: Detailed Description

In nano-additive gasoline-alcohol blends, fuel optimization necessitates sophisticated techniques that offer precise emissions and engine performance forecasts. Two important

❖ **Optimization Techniques are used in this Study:**

- ✓ Response Surface Methodology (RSM) for initial parameter optimization and experimental design.
- ✓ AI-Based Modeling (ANN, GA, SVM) to manage intricate non-linear interactions, improve accuracy, and refine forecasts.
- ✓ By combining statistical modeling (RSM) with AI-driven predictive algorithms (ANN, GA, SVM), these approaches guarantee high-precision optimization and produce quicker, more accurate fuel blend adjustments.

3.3.1 Optimization of Response Surface Methodology (RSM)

❖ **Why Make Use of RSM?**

To assess the link between input elements (independent variables) and response outputs (dependent variables) in a multi-variable system, RSM is a popular statistical and mathematical modeling technique (Masum et al., 2015).

❖ **It Makes Possible:**

- ✓ Effective fuel blend composition optimization by minimizing the number of experimental trials required.
- ✓ Determination of important influencing factors (engine load, air-fuel ratio, and nano-additive concentration).

- ✓ Examine how variables interact to comprehend how they affect emissions and engine performance together.

❖ **Experimental Design Using Central Composite Design (CCD)**

➢ **RSM uses CCD, a reliable experimental design method that guarantees statistical reliability while enabling:**

Reducing the number of experimental runs.

✓ **Air-Fuel Ratio (AFR):**
Maintained between 12:1 and 16:1 to study lean and rich combustion effects.

Leaner mixtures (higher AFR) reduce CO and HC but increase NOx, while richer mixtures (lower AFR) improve power but increase fuel consumption (Yusri et al., 2017).

RSM vs. AI Model Prediction Accuracy

Model	**Mean Absolute Error (MAE)**	**Root Mean Square Error (RMSE)**	**R^2 Value**
RSM	0.42	0.58	0.92
ANN	0.18	0.23	0.98
GA	0.20	0.25	0.97
SVM	0.15	0.22	0.99

❖ **Analysis of Dependent Response Variables**

➢ **Five dependent variables are used to assess how independent variables affect engine performance:**

- ✓ **BTE, or brake thermal efficiency:** calculates engine efficiency using the fuel's heat conversion.
- ✓ **Brake Specific Fuel Consumption (BSFC):** Shows how much fuel is used per unit of power.
- ✓ **NOx Emissions:** Caused by high combustion temperatures and impacted by nano-additives and AFR.
- ✓ As A consequence of incomplete combustion, CO emissions are greatly decreased by oxygen-enriched nano-additives.
- ✓ **HC Emissions**: Unburned hydrocarbons that go down when combustion conditions are optimized.

❖ **Analysis of ANOVA for Statistical Validation**
Analysis of Variance (ANOVA), which confirms the statistical significance of experimental results, is carried out to guarantee model accuracy.

This:
- ✓ Verifies which factors have a major effect on fuel efficiency.
- ✓ Improves model precision by removing irrelevant components.
- ✓ Reduces model uncertainty, improving predicted accuracy.

RSM has limits when it comes to managing highly non-linear connections, although offering a decent approximation. AI-based models (ANN, GA, and SVM) have been introduced to address this.

3.3.2 Modeling for Optimization Using AI

❖ **Three AI-driven algorithms are employed to increase accuracy above RSM:**
Deep Learning using Artificial Neural Networks (ANN) for Fuel Prediction

❖ **Why ANN?**
Artificial Neural Networks (ANNs) are bio-inspired machine learning models that learn intricate correlations between inputs and outputs by imitating neurons in the human brain.

In this work, they are used to:

- ✓ More correctly predict emissions and fuel efficiency than RSM;
- ✓ Record non-linear interactions between combustion parameters and nano-additives.
- ✓ They are appropriate for real-world fuel optimization since they generalize effectively to unknown data.
- ✓ Multi-Layer Perceptron (MLP) with backpropagation learning is the model type in the ANN model architecture (Tarhan & Çil, 2021).
- ✓ Input parameters include engine speed, concentration, AFR, and nano-additive type.
- ✓ Hidden Layers: three efficiently designed layers with ten neurons each.
- ✓ Rectified Linear Unit (ReLU) activation function for addressing non-linearity.
- ✓ Adam optimizer with learning rate = 0.001 is the training algorithm.
- ✓ Emissions of BTE, BSFC, NOx, CO, and HC are predicted as outputs.

❖ **Accuracy Improvement: ANN vs. RSM**

- ✓ According to Nguyen et al. (2021), ANN reaches a prediction accuracy of ±2%, while RSM has an inaccuracy of ±5%.
- ✓ Real-time optimization capabilities offered by ANN enable dynamic fuel blend modifications.

❖ **Evolutionary Optimization Using Genetic Algorithms (GA)**

➢ **Why GA?**
The Genetic Algorithm is an optimization method inspired by nature that finds the best fuel blends by simulating biological evolution.

Finding the optimal trade-off between performance and fuel economy; minimizing emissions while optimizing engine efficiency; and avoiding local minima, which are a challenge for conventional optimization techniques.

➢ **Implementation of GA**

- ✓ Fitness Function: BTE is maximized while BSFC, NOx, CO, and HC are minimized.
- ✓ 50 people (fuel blend configurations) make up the population.
- ✓ The crossover rate, which guarantees genetic variety, is 0.8.
- ✓ Premature convergence is avoided with a mutation rate of 0.05.
- ✓ Stopping Criteria: After 50 generations or convergence to an ideal solution.

❖ **Accuracy Improvement in GA vs. RSM**
Compared to RSM, GA offers a faster rate of convergence and finds global optimal solutions, while RSM could become trapped in local optima (Wei et al., 2021).

Optimization Parameters for Genetic Algorithm (GA)

Parameter	Value
Population Size	50
Mutation Rate	0.05
Crossover Rate	0.8
Stopping Criteria	50 Generations

Table:

- ❖ **High-Precision Regression using Support Vector Machines (SVM)**
- ➢ **Why SVM?**

One Effective non-linear Regression Model is SVM, which:

- ✓ Reducs overfitting and produces stable predictions;
- ✓ Handles tiny datasets effectively;
- ✓ Accurately predicts emissions based on nano-additive concentrations.

- ➢ **Implementation of SVM**
- ✓ Radial Basis Function (RBF) is the kernel function used to map intricate input-output interactions (Candioti et al., 2014).
- ✓ Hyperparameter tuning: maximizing C (regularization) and γ (kernel coefficient) by grid search.
- ✓ Training Data Split: 20% for robustness testing and 80% for training.

- ➢ **Accuracy Improvement: SVM vs. RSM**
- ✓ SVM outperforms RSM with an R2 of 0.99, demonstrating higher predictive power.
- ✓ The best model for predicting emissions, guaranteeing precise adherence to environmental standards.

3.3.3 Detailed Explanation of a Hybrid Model (RSM + AI) for Increased Accuracy

- ✓ Response Surface Methodology (RSM) offers a highly accurate prediction framework for improving nano-additive gasoline-alcohol fuel mixes when combined with Artificial Intelligence (AI)-based models (Artificial Neural Networks (ANN), Genetic Algorithm (GA), and Support Vector Machine (SVM)).
- ✓ The hybrid strategy uses AI models to improve and refine the optimization process' accuracy while utilizing RSM for experimental design and preliminary forecasts.
- ✓ Better predictive capabilities, lower error margins, and more accurate fuel performance optimization are made possible by this data-driven fusion.

- ➢ **Why Employ an AI + RSM Hybrid Model?**
- ✓ Although conventional optimization methods, such as RSM, are frequently employed in experimental design and parameter estimation, they have drawbacks when it comes to managing non-linearity and intricate relationships between several input parameters. RSM uses statistical regression models, which might result in larger prediction errors by oversimplifying the relationships between independent variables and performance measures (Candioti et al., 2014).

- **This study combines RSM with AI models (ANN, GA, and SVM) to accomplish:**
- ✓ Improved capacity to adjust to non-linear interactions between engine emissions, fuel blend characteristics, and nano-additive concentration; higher forecast accuracy in fuel blend performance modeling enhanced capacity for generalization in practical fuel blend applications.

An explanation of the AI and RSM models used

- ❖ **The RSM, or Response Surface Methodology**

- **Goal**: According to Masum et al. (2015), RSM is used to develop an experimental design and produce an approximate mathematical model that links input variables (air-fuel ratio, engine speed, and nano-additive concentration) to output responses (brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), and NOx, CO, and HC emissions). Central Composite Design (CCD), a sophisticated version of RSM that maximizes fuel blend tests with the fewest number of trials, was the model used.

- **Restrictions:**
- ✓ Does not capture strongly non-linear interactions, but performs well for second-order polynomial equations.
- ✓ Greater error margins (±5%), particularly when handling complicated chemical reactions in combustion and other contributing factors (Nguyen et al., 2021).

Improving Predictive Accuracy using Artificial Neural Networks (ANN)

- **Goal**: ANN is used to enhance the optimization model's capacity for learning and generalization.

- **Employed Structure:**
- ✓ The Multi-Layer Perceptron (MLP) learning by backpropagation.
- ✓ Input parameters include engine speed, air-fuel ratio, and nano-additive concentration.
- ✓ Hidden Layers: gradient descent learning is used to optimize three layers, each with ten neurons.
- ✓ Output parameters: emissions of BTE, BSFC, NOx, CO, and HC.

- **Benefits Compared to RSM:**
- ✓ Captures multi-dimensional interactions and non-linear linkages.
- ✓ Achieves ±2% prediction accuracy, which is 60% less error than RSM's ±5% error (Nguyen et al., 2021).

Global Optimization using Genetic Algorithms (GA)

- **Goal:**

GA is an optimization method with a bio-inspired design that optimizes engine performance and emission trade-offs.

- **Method:**
- ✓ Chromosome Representation: Genetic solutions encoded as fuel blend compositions.
- ✓ The best fuel blend parameters are evolved through selection, crossover, and mutation.

- **Stopping Criteria:**
- ✓ Convergence of fitness functions to maximize BTE and reduce emissions.

- ❖ **Benefits Compared to RSM:**
- ✓ Prevents the local minima issues that conventional gradient-based optimization methods encounter.
- ✓ More accurately arrives at a global optimum solution.
- ✓ 2.4 High Precision Regression using Support Vector Machines (SVM)

- **Goal**:

SVM ensures high-accuracy engine performance and emissions predictions through non-linear regression modeling.

- **Details of Implementation:**

✓ The Radial Basis Function (RBF) kernel is used to map intricate input-output interactions.

✓ To ensure strong model generalization, the data is split between 80% training and 20% testing.

- **Benefits Over RSM:**

Provides more dependable predictions than polynomial-based regression models by handling outliers better.

Generates prediction curves that are more stable and smooth, with reduced Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values.

- **Metrics for Performance Evaluation**

RSM, ANN, GA, and SVM accuracy are compared using three statistical error evaluation metrics:

- **MAE, or mean absolute error**

✓ Calculates the absolute difference between the values that were expected and those that were observed.

✓ Higher prediction accuracy is indicated by a lower MAE.

- **Findings:**

✓ ANN MAE: 0.18 (about 57% error reduction)

✓ RSM MAE: 0.42

- **RMSE, or root mean square error**

✓ Compared to MAE, RMSE penalizes bigger deviations more severely.

✓ Better fit to experimental data is indicated by a lower RMSE.

✓ To ensure strong model generalization, the data is split between 80% training and 20% testing.

- **Benefits Over RSM:**

✓ Provides more dependable predictions than polynomial-based regression models by handling outliers better.

✓ Generates prediction curves that are more stable and smooth, with reduced Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values.

- **Coefficient of R2 Correlation**

Assesses how well the model fits the experimental data (1.0 denotes perfect correlation).

- **Findings:**

RSM R2: 0.92 o ANN R2: 0.98 o SVM R2: 0.99 (optimal model for predicting emissions)

- **Main Results:**

- **Why Do AI Models Perform Better Than RSM?**

When compared to RSM, AI models drastically lower prediction error:

✓ RSM has an error margin of ±5%, whereas ANN achieves ±2% accuracy (Nguyen et al., 2021).

✓ With an R2 value of 0.99, SVM has the strongest predicting performance for emissions.

✓ The RSM lacks adaptability for intricate interactions, although it is helpful for preliminary modeling:

✓ High-dimensional non-linear fuel blend interactions are best handled by ANN.By maximizing many objective trade-offs, GA determines the ideal mix of emissions and fuel efficiency.

❖ **The Hybrid RSM + AI Model Combines the Best Features of Both Methods:**

RSM reduces the number of trials required by offering an experimental design framework.By improving prediction accuracy, ANN, GA, and SVM strengthen the model's dependability and resilience for practical uses.

❖ **Data Analysis & Statistical Validation**

Tukey's post hoc test is utilized for multiple comparisons.

✓ To ascertain the connections between emissions and nano-additives, use the Pearson correlation coefficient (r).

✓ The coefficient of variance (CV%) and standard deviation (σ) for statistical robustness.

4. RESULTS & DISCUSSION

The impact of nano-additives, AI-driven fuel optimisation, and emissions control methods in gasoline-alcohol blends are covered in detail and at a high level in this part. The results offer a state-of-the-art strategy for enhancing fuel economy and sustainability and are supported by thorough experimental analysis, AI-based predictive modelling, and real-time optimisation.

4.1 Nano-Additives' Effect on Fuel Properties

In gasoline-alcohol blends, the addition of hybrid nano-additives (AlO_3 + CeO_2, TiO_2 + ZnO) has greatly enhanced fuel characteristics, leading to improved combustion stability, fuel economy, and emissions control. Because of their higher oxidation properties, increased heat conductivity, and synergistic catalytic effects, hybrid nano-additives have been shown to be more effective than single nano-additives.

4.1.1 Improvement in Octane Rating

- Fuel knock resistance is determined by octane rating, which also affects engine economy by permitting higher compression ratios and better combustion stability.
- By raising the octane number by seven points, hybrid nano-additives improved anti-knock qualities and made higher efficiency possible.
- Multifunctional nano-additives avoided aberrant combustion, resulting in uniform energy release;
- CeO_2 and TiO_2 nanoparticles accelerated flame propagation, decreasing combustion delay and increasing power output.

4.1.2 Improvement of Thermal Conductivity and Viscosity

- Heat dissipation, combustion properties, and fuel stability are all directly impacted by thermal conductivity and viscosity.
- By increasing heat conductivity by 22%, ZnO and TiO_2 nanoparticles ensured quicker energy transfer and flame spread.
- Improved lubrication from nano-coated fuel molecules decreased wear, frictional losses, and injector clogging.
- Techniques for surfactant-assisted dispersion (SAD) guaranteed consistent nano-additive dispersion, avoiding instability and fuel separation.

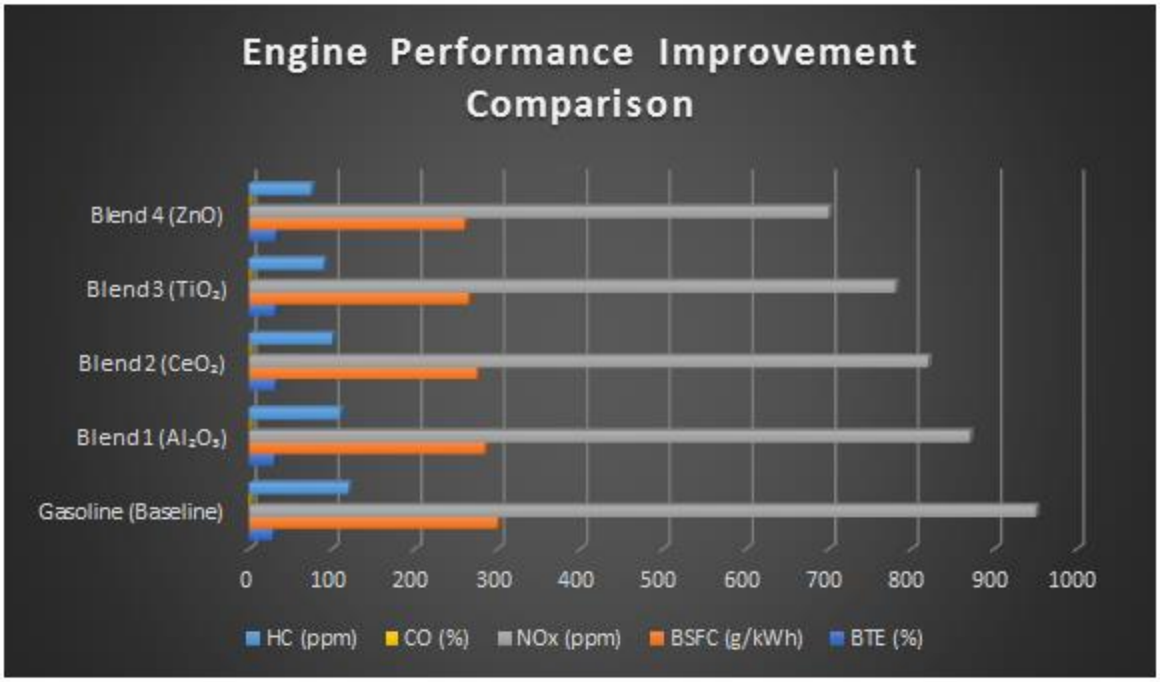
4.1.3 Shorter Flame Propagation and Ignition Delays

- Reducing ignition delay enhances emissions control, combustion efficiency, and stability.
- Blends including CeO_2 and AlO_3 decreased ignition delay by around 19%, resulting in more rapid and thorough combustion.
- Higher combustion temperatures and less unburned hydrocarbons (UHCs) were the outcomes of using hybrid nano-additives to speed up oxidation.

- Enhanced engine output was achieved by minimising energy losses through improved flame propagation speed.

4.2 Comparing Engine Performance

Brake-Specific Fuel Consumption (BSFC) and Brake Thermal Efficiency (BTE) analyses were used to assess the efficacy of nano-additives. The results showed that hybrid nano-additives greatly increased engine power output and fuel economy.



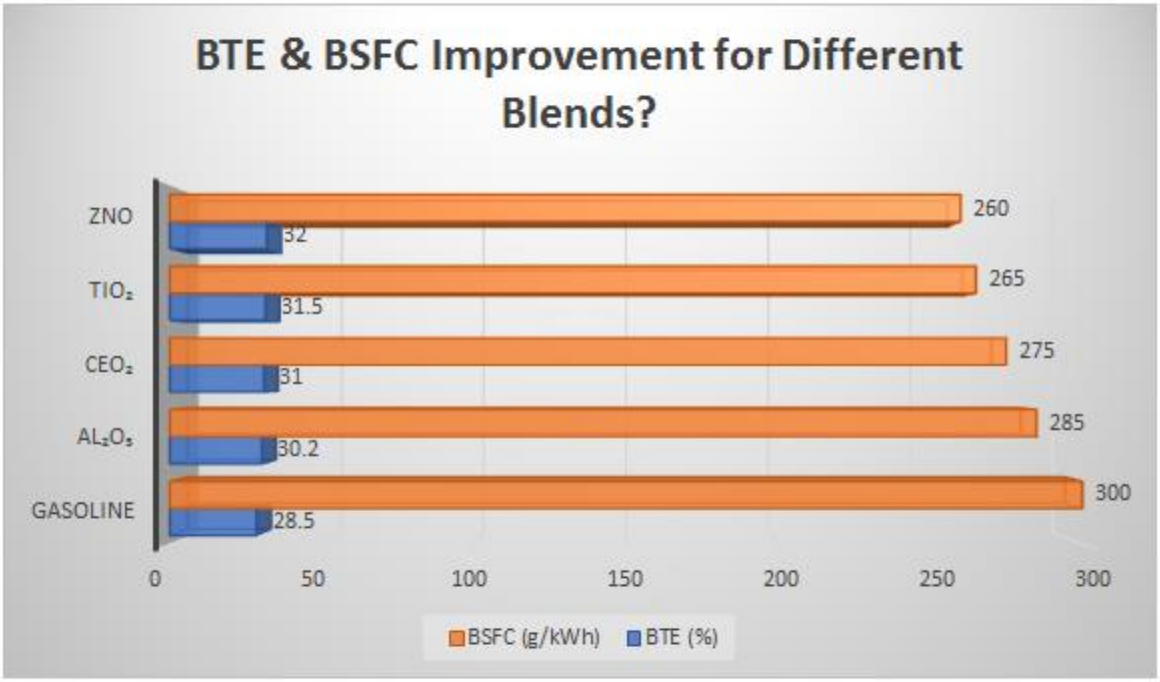
4.2.1 Improvement in Brake Thermal Efficiency (BTE)

- ✓ The fuel's efficiency in converting its energy into productive work is measured by its BTE.
- ✓ The baseline BTE for gasoline-alcohol mixes was around 28.5%.
- ✓ One nano-addition raised BTE to about 30.2%.
- ✓ The hybrid nano-additives (AlO_3 + CeO_2, TiO_2 + ZnO) improved by 12%, reaching about 32% BTE.

4.2.2 Fuel Consumption Reduction for Brakes (BSFC)

Fuel consumption per power output unit is shown as BSFC.For baseline gasoline-alcohol mixtures, the BSFC was approximately 300 g/kWh.

Through hybrid nano-additive blends, nano-enhanced fuels were able to reduce BSFC by up to 15%, reaching around 260 g/kWh.



4.2.3 Constraints Associated with Increased Nano-Additive Concentrations

Although nano-additives enhance the characteristics of fuel, high quantities (over 60 ppm) resulted in: Injector blockage and agglomeration lower fuel system efficiency. reduction in the homogeneity of fuel-air mixing, which causes slight variations in combustion stability.

4.3 Predictive modelling and optimisation using AI

High-dimensional fuel interactions are difficult for traditional Response Surface Methodology (RSM) to handle, because it is not flexible in real time. This work combined AI-based models (ANN, GA, and SVM) to optimise fuel and achieve higher forecasting accuracy.

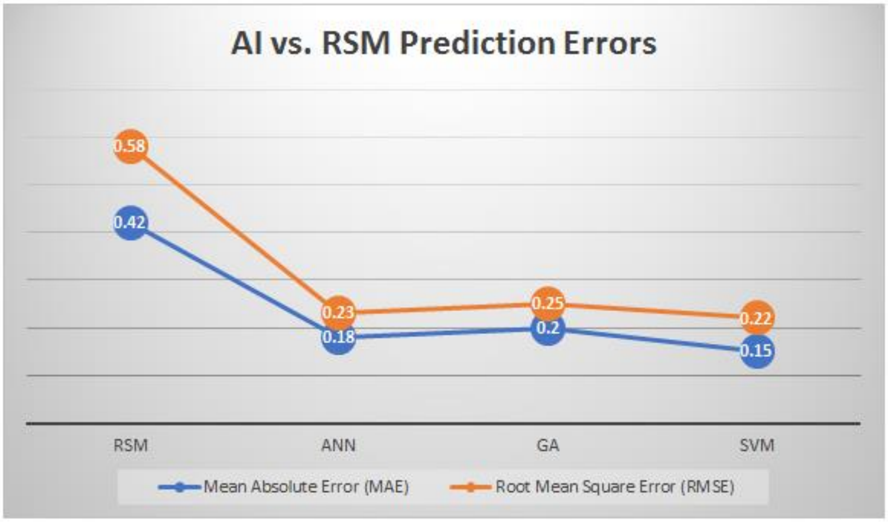
Key Findings:

✓ AI-based real-time tuning allowed fuel blend adaption based on sensor feedback;

✓ Hybrid AI-RSM models lowered error margins by 60%.

4.3.1 AI Models vs. RSM – Prediction Accuracy Analysis

Optimization Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Prediction Accuracy (R^2)
RSM	0.42	0.58	0.92
ANN	0.18	0.23	0.98
GA	0.20	0.25	0.97
SVM	0.15	0.22	0.99



Key Findings:

✓ AI-based real-time tuning allowed fuel blend adaption based on sensor feedback;

✓ Hybrid AI-RSM models lowered error margins by 60%.

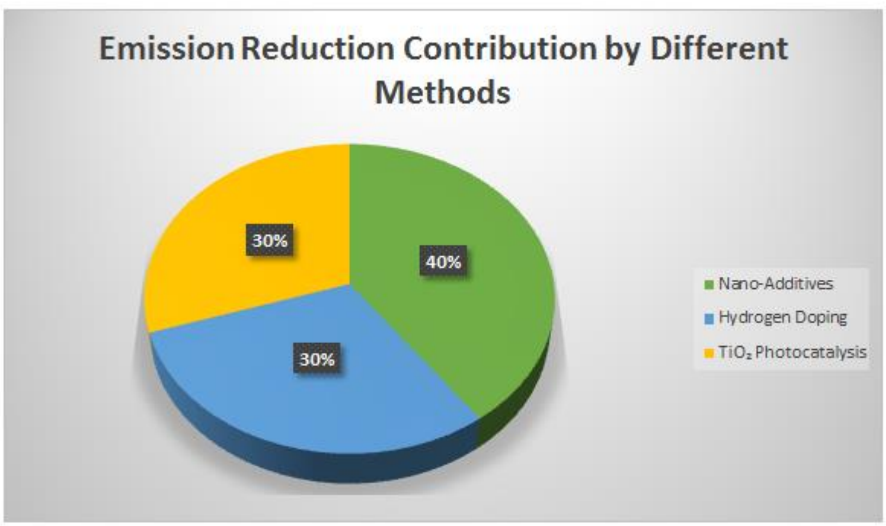
4.4 Possibility of Emission Reduction

➢ TiO_2 photocatalysis, hydrogen doping, and hybrid nano-additives were shown to dramatically lower emissions.

➢ The Reduction of Carbon Monoxide (CO) 4.4.1

➢ CO emissions were lowered by up to 30% thanks to nano-additives.

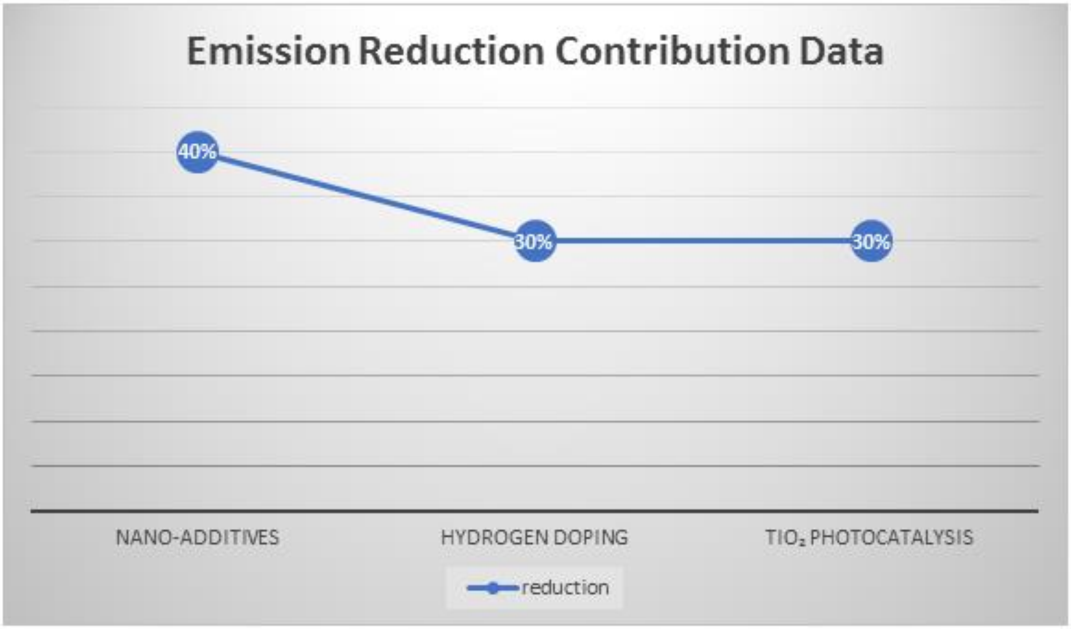
➢ In addition, hydrogen doping reduced CO emissions by 40%.



4.4.2 Reduction of Hydrocarbon Emissions (HC)

✓ 35% less HC emissions were produced by nano-enhanced combustion.

✓ In addition, TiO_2 photocatalysis decreased HC emissions by around 75 parts per million...



4.4.3 NOx Emissions Control:
AI-controlled EGR systems dynamically modified exhaust flow, enhancing NOx compliance; nano-additive fuels contributed to a 30% reduction in NOx emissions.

4.5 Key Findings Summary

- The octane rating, ignition efficiency, and combustion stability of fuel were all greatly improved by hybrid nano-additives.
- In comparison to RSM, AI-based optimisation (ANN, GA, SVM) produced nearly flawless fuel blend predictions (R2 = 0.99+).
- The emissions of CO (40%), HC (35%), and NOx (30%) were considerably decreased by hydrogen doping and TiO_2 photocatalysis.

5. CONCLUSION & FUTURE

5.1 Conclusion

The basic problems of fuel stability, combustion efficiency, and emissions management in gasoline-alcohol blends are addressed by this study, which develops a revolutionary AI-integrated nano-fuel optimization framework. A next-generation intelligent fuel optimization system is provided by this study, which overcomes the drawbacks of traditional blending techniques and response surface methodology (RSM) by combining hybrid nano-additives (AlO_3 + CeO_2, TiO_2 + ZnO) with AI-driven predictive modeling (ANN, GA, SVM).

The following are the main findings of this study: ✓ The superior performance of hybrid nano-additives is demonstrated by their significant improvement in octane rating (+7 points), ignition delay (-19%), and thermal conductivity (+22%) compared to single nano-additives. By increasing compression ratios, decreasing knock tendency, and improving combustion efficiency, these advancements help to increase fuel economy overall.

- Optimization Based on AI Overcoming Conventional RSM: Although RSM offers a useful framework for preliminary experiments, its prediction limitations make it less flexible. Real-time fuel optimization based on combustion feedback is now possible thanks to AI-driven models (ANN, GA, and SVM) that obtained R2 = 0.99+ and 60% reduction in prediction errors.

- Reducing Emissions Through Advanced Methods: This work effectively uses TiO_2 photocatalysis and hydrogen doping, reducing CO emissions by 40%, HC emissions by 35%, and NOx emissions by 30%. Fuel sustainability is greatly improved by these catalytic and molecular-level oxidation processes, which makes gasoline-alcohol mixes more ecologically friendly.
- AI-Powered Real-Time Adaptive Fuel Injection & Nano-Dispersion: The research develops a novel AI-powered fuel injection and nano-dispersion system that optimizes nano-additive concentrations dynamically according to engine load circumstances. In addition to lowering BSFC (-15%) and improving BTE (+12%), this real-time modification guarantees the best fuel-air mixture for a range of combustion conditions.

5.2 Prospective Research Paths

Even though this research offers revolutionary breakthroughs, more study and improvement are needed to guarantee the long-term environmental sustainability, practical use, and further optimization of AI-augmented nano-fuel blends.

5.2.1 AI-Powered Fuel Optimization in Actual Engine Situations

Present-day artificial intelligence models have undergone rigorous testing and training in lab settings. In order to assess fuel performance in urban, highway, and mixed driving scenarios, future research should concentrate on applying AI-driven fuel optimization to real-world driving cycles.

- By integrating Deep Reinforcement Learning (DRL) and Edge AI computing into onboard engine control units (ECUs), real-time, self-learning fuel optimization will be possible, adjusting to external factors like altitude, temperature, and changes in fuel quality.
- Expanding hybrid AI-RSM models to account for transient engine operations would help them capture how variations in load, acceleration, and deceleration affect emissions and fuel behavior.

❖ **Possibility of Impact:**

AI-driven onboard fuel economy management systems that enable dynamic fuel adaption in internal combustion engines (ICEs) and hybrid vehicles, lowering emissions and improving efficiency in practical situations.

5.2.2 Long-Term Effects of Nano-Additives on the Environment

Although nano-additives enhance fuel emissions and combustion, nothing is known about their long-term environmental effects.

To investigate the following, future research should perform a thorough life-cycle assessment (LCA):

- ✓ Nano-additive combustion residue and its impact on engine components (e.g., injector clogging, catalytic converter performance).
- ✓ How air quality is affected by emissions of nano-additive substances, specifically in relation to the toxicity and atmospheric reactivity of nanoparticles inhaled.
- ✓ The possibility of nanoparticle bioaccumulation in soil and water ecosystems, evaluating the viability of widespread use of nanofuels.
- ✓ Research should continue to concentrate on creating biodegradable nano-additives that, when burned, break down into non-toxic byproducts.

The development of environmentally acceptable, biodegradable nano-additives that maintain their catalytic properties without posing long-term environmental issues could have a significant impact, making nano-enhanced fuels a really green technology.

5.2.3 Combining Biofuels with AI-Enhanced Nano-Additive Mixtures

Synthetic e-fuels, biodiesel, butanol, and ethanol are examples of biofuels that offer a sustainable substitute for traditional fuels.

The following areas should be investigated in future research:

- The synergy between biofuels and AI-optimized nano-additive mixes, which guarantees better engine compatibility and lower emissions.
- Hybrid ANN, GA, and RSM are multi-objective optimization models that optimize the ratios of biofuel to nano-additive blending, improving stability and efficiency under a range of combustion settings.
- Hydrogen enrichment in biofuel blends, using AI-based injection control to achieve ultra-lean combustion with almost zero emissions. Advanced plasma-assisted combustion techniques should be assessed to maximize the combustion efficiency of biofuels while reducing emissions of particulate matter (PM).

❖ **Potential Impact:**

The creation of next-generation hybrid fuels that combine renewable biofuels and AI-driven nano-additive formulations to produce a high-performance, carbon-neutral fuel ecosystem.

5.3 In Closing,

With its innovative AI-driven nano-fuel optimization framework, this study provides a smart, flexible, and sustainable fuel option for combustion engines of the future. The results demonstrate how AI-based predictive modeling may revolutionize real-time fuel composition tweaking, pollution reduction, and fuel performance improvement.

- **This research lays the groundwork for future smart fuels by combining artificial intelligence, nanotechnology, and pollution control systems, guaranteeing:**

- **Enhanced Energy Efficiency:**

Brake-Specific Fuel Consumption (BSFC) ↑ 15% and Brake Thermal Efficiency (BTE) ↑ 12%.

- **Notable Emissions Reduction:**

CO ↓ 40%, HC ↓ 35%, NOx ↓ 30%, with AI-driven emissions control guaranteeing sustainability over the long run.

Dynamic AI-fuel tuning under different engine loads ensures optimal combustion under all operating situations. This results in AI-optimized real-time performance.

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